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## Determining the difficulty of Word Sense Disambiguation

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## ABSTRACT

Automatic processing of biomedical documents is made difficult by the fact that many of the terms they contain are ambiguous. Word Sense Disambiguation (WSD) systems attempt to resolve these ambiguities and identify the correct meaning. However, the published literature on WSD systems for biomedical documents report considerable differences in performance for different terms. The development of WSD systems is often expensive with respect to acquiring the necessary training data. It would therefore be useful to be able to predict in advance which terms WSD systems are likely to perform well or badly on.

This paper explores various methods for estimating the performance of WSD systems on a wide range of ambiguous biomedical terms (including ambiguous words/phrases and abbreviations). The methods include both supervised and unsupervised approaches. The supervised approaches make use of information from labeled training data while the unsupervised ones rely on the UMLS Metathesaurus. The approaches are evaluated by comparing their predictions about how difficult disambiguation will be for ambiguous terms against the output of two WSD systems. We find the supervised methods are the best predictors of WSD difficulty, but are limited by their dependence on labeled training data. The unsupervised methods all perform well in some situations and can be applied more widely.

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## 1. Introduction

Word Sense Disambiguation (WSD) is the task of automatically identifying the appropriate sense of an ambiguous word based on the context in which the word is used. For example, the term *cold* could refer to the *temperature* or the *common cold*, depending on how the word is used in the sentence. Automatically identifying the intended sense of ambiguous words improves the performance of biomedical and clinical applications such as medical coding and indexing; applications that are becoming essential tasks due to the growing amount of information available to researchers.

A wide range of approaches have been applied to the problem of WSD in biomedical and clinical documents [1–7]. Accurate WSD can improve the performance of biomedical text processing applications, such as summarization [8], but inaccurate WSD has been shown to reduce an application's overall performance [9]. The disambiguation of individual terms is important since some of those terms are more important than others when determining whether there is any overall improvement of the system [8]. The

importance of WSD is likely to depend on the application and research question. For example, Weeber et al. [10] found that it was necessary to resolve the ambiguity in the abbreviation “MG” (which can mean “magnesium” or “milligram”) in order to replicate the connection between migraine and magnesium identified by Swanson [11].

It is now possible to perform very accurate disambiguation for some types of ambiguity, such as abbreviations [12]. However, there is considerable difference in the performance of WSD systems for different ambiguities. For example, Humphrey et al. [3] report that the performance of their unsupervised WSD approach varies between 100% (for terms such as *culture* and *determination*) and 6% (for *fluid*). Consequently, it is important to determine the accuracy of a WSD system for the ambiguities of interest to get an idea of whether it will be useful for the overall application, and if so, which terms should be disambiguated.

Historically, supervised machine learning approaches have been shown to disambiguate terms with a higher degree of accuracy than unsupervised methods. The disadvantage to supervised methods is that they require manually annotated training data for each term that needs to be disambiguated. However, manual annotation is an expensive, difficult and time-consuming process which is not practical to apply on a large scale [13]. To avoid this problem, techniques for automatically labeling terms with senses have

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been developed [12,14] but these can only be applied to limited types of ambiguous terms, such as abbreviations and terms which occur with different MeSH codes. Therefore, it would be useful to be able to predict the difficulty of a particular term in order to determine whether applying WSD would be of benefit to the overall system.

This paper explores approaches to estimating the difficulty of performing WSD on ambiguities found in biomedical documents. By difficulty we mean the WSD performance that can be obtained for the ambiguity since, in practise, performance is the most important factor in determining whether applying WSD to a particular ambiguity is likely to be useful. Ambiguities for which low WSD performance is obtained are considered to be difficult to disambiguate while those for which the performance is high are considered to be easy to disambiguate.

Some of the methods applied in this paper are supervised since they are based on information derived from a corpus containing examples of the ambiguous term labeled with the correct sense. Other methods do not require this resource and only require information about the number of possible senses for each ambiguous term which is normally obtained from a knowledge source, such as the UMLS Metathesaurus (see Section 2.1.1).

Section 2 provides background information on relevant resources and techniques for computing similarity or relatedness in the biomedical domain. Section 3 describes a range of methods for estimating WSD difficulty, including ones that have been used previously and an unsupervised method based on the similarity/relatedness measures described in Section 2. Experiments to evaluate these are described in Section 4 and their results in Section 5. Finally, conclusions are presented in Section 6.

## 2. Resources and background

### 2.1. Resources

This section presents the resources that are used in the experiments described later in the paper. In particular, they are used by the similarity and relatedness measures described in Sections 2.2.1 and 2.2.2.

#### 2.1.1. Unified Medical Language System

The Unified Medical Language System (UMLS) is a repository that stores a number of distinct biomedical and clinical resources. One such resource, used in this work, is the Metathesaurus [15].

The Metathesaurus contains biomedical and clinical concepts from over 100 disparate terminology sources that have been semi-automatically integrated into a single resource containing a wide range of biomedical and clinical information. For example, it contains the Systematized Nomenclature of Medicine–Clinical Terms (SNOMED CT), which is a comprehensive clinical terminology created for the electronic exchange of clinical health information, the Foundational Model of Anatomy (FMA), which is an ontology of anatomical concepts created specifically for biomedical and clinical research, and MedlinePlus Health Topics, which is a terminology source containing health related concepts created specifically for consumers of health services.

The concepts in these sources can overlap. For example, the concept *Cold Temperature* exists in both SNOMED CT and MeSH. The Metathesaurus assigns the synonymous concepts from the various sources Concept Unique Identifiers (CUIs). Thus both the *Cold Temperature* concepts in SNOMED CT and MeSH are assigned the same CUI (C0009264). This allows multiple sources in the Metathesaurus to be treated as a single resource.

Some sources in the Metathesaurus contain additional information such as a concept's synonyms, its definition,<sup>1</sup> and its related concepts. The Metathesaurus contains a number of relations. The two main hierarchical relations are: the parent/child (PAR/CHD) and broader/narrower (RB/RN) relations. A parent/child relation is a hierarchical relation between two concepts that has been explicitly defined in one of the sources. For example, the concept *Cold Temperature* has an *is-a* relation with the concept *Freezing* in MeSH. This relation is carried forward to the CUI level creating a parent/child relations between the CUIs C0009264 [Cold Temperature] and C0016701 [Freezing] in the Metathesaurus. A broader/narrower relation is a hierarchical relation that does not explicitly come from a source but is created by the UMLS editors. For this work, we use the parent/child relations.

#### 2.1.2. MEDLINE

MEDLINE<sup>2</sup> is a bibliographic database that currently contains over 22 million citations to journal articles in the biomedical domain and is maintained by the National Library of Medicine (NLM). The 2009 MEDLINE Baseline Repository<sup>3</sup> encompasses approximately 5200 journals starting from 1948 and contains 17,764,826 citations; consisting of 2,490,567 unique unigrams (single words) and 39,225,736 unique bigrams (two-word sequences). The majority of the publications are scholarly journals but a small number of other sources such as newspapers and magazines are included.

#### 2.1.3. UMLSonMedline

UMLSonMedline, created by NLM, consists of concepts from the 2009AB UMLS and the number of times they occurred in a snapshot of MEDLINE taken on 12/01/2009. The frequency counts were obtained by using the Essie Search Engine [16] which queried MEDLINE with normalized strings from the 2009AB MRCONSO table in the UMLS. The frequency of a CUI was obtained by aggregating the frequency counts of the terms associated with the CUI to provide a rough estimate of its frequency.

#### 2.1.4. Medical Subject Headings (MeSH)

The Medical Subject Headings (MeSH) Thesaurus ([17]) is the NLM's controlled vocabulary thesaurus consisting of biomedical and health related terms/concepts created for the purpose of indexing articles from MEDLINE. Each MEDLINE citation is associated with a set of manually annotated MeSH terms that describe the content of the article. The MeSH terms are organized in a hierarchical structure in order to permit searching at various levels of specificity. The 2013 version contains 26,853 terms organized into 11 different hierarchies.<sup>4</sup>

### 2.2. Measures of similarity and relatedness

This section described measures of similarity and relatedness between biomedical concepts that have been previously explored in the literature.

#### 2.2.1. Similarity measures

Existing semantic similarity measures can be categorized into two groups: path-based and information content (IC)-based. Path-based measures use information about the number of nodes between concepts in a hierarchy, whereas IC-based measures incorporate the probability of the concept occurring in a corpus of text.

<sup>1</sup> Not all concepts in the UMLS have a definition.

<sup>2</sup> <http://www.ncbi.nlm.nih.gov/pubmed/>.

<sup>3</sup> <http://mbr.nlm.nih.gov/>.

<sup>4</sup> <http://www.nlm.nih.gov/pubs/factsheets/mesh.html>.

**Path-based Similarity Measures** Rada et al. [18] introduce the conceptual distance measure which is the length of the shortest path between two concepts ( $c_1$  and  $c_2$ ) in MeSH using RB/RN relations from the UMLS. Caviedes and Cimino [19] later adapted this measure using the PAR/CHD relations in the UMLS.

Our first measure, *path*, is a modification of Caviedes and Cimino's approach. Similarity is defined as the reciprocal of the length of the shortest path between the two concepts in the UMLS hierarchy. This is shown in Eq. (1), where  $path\_length(c_1, c_2)$  is the number of nodes in the shortest path between  $c_1$  and  $c_2$ .

$$sim_{path}(c_1, c_2) = \frac{1}{path\_length(c_1, c_2)} \quad (1)$$

Wu and Palmer [20] extend this measure by incorporating the depth of the Least Common Subsumer (LCS). The LCS of a pair of concepts is the lowest concept in the hierarchy which subsumes that pair. In this measure, the similarity is twice the depth of the two concepts LCS divided by the product of the depths of the individual concepts as defined in Eq. (2), where *depth* is the number of nodes between  $c$  and the root node in the hierarchy.

$$sim_{wup}(c_1, c_2) = \frac{2 * depth(lcs(c_1, c_2))}{depth(c_1) + depth(c_2)} \quad (2)$$

**IC-based Similarity Measures** Information content (IC) is formally defined as the negative log of the probability of a concept [21]. The probability of a concept,  $c$ , is obtained by summing the number of times it or one of its descendants is seen in a corpus. The concepts descendants are obtained from some concept hierarchy, such as one of those contained in the UMLS Metathesaurus. Very general concepts have high probabilities since their descendants are mentioned frequently and this leads to them having low IC values. Conversely, specific concepts have low probabilities and high IC values. Resnik [22] modified IC for use as a similarity measure. He defined the similarity of two concepts to be the IC of their LCS, see Eq. (3).

$$sim_{res}(c_1, c_2) = IC(lcs(c_1, c_2)) = -\log(P(lcs(c_1, c_2))) \quad (3)$$

Jiang and Conrath [23] and Lin [24] extended Resnik's IC-based measure by incorporating the IC of the individual concepts. Lin defined the similarity between two concepts by taking the quotient between twice the IC of the concepts' LCS and the sum of the IC of the two concepts as shown in Eq. (4). This is similar to the measure proposed by Wu and Palmer; differing in the use of IC rather than the depth of the concepts.

$$sim_{lin}(c_1, c_2) = \frac{2 * IC(lcs(c_1, c_2))}{IC(c_1) + IC(c_2)} \quad (4)$$

Jiang and Conrath defined the distance between two concepts to be the sum of the IC of the two concepts minus twice the IC of the concepts' LCS. This measure is often modified to return a similarity score by taking the reciprocal of the distance as shown in Eq. (5).

$$sim_{jcn}(c_1, c_2) = \frac{1}{IC(c_1) + IC(c_2) - 2 * IC(lcs(c_1, c_2))} \quad (5)$$

### 2.2.2. Relatedness measures

Lesk [25] introduces a measure that determines the relatedness between two concepts by counting the number of shared terms in their definitions. An overlap is the longest sequence of one or more consecutive words that occur in both definitions. When implementing this measure in WordNet, Banerjee and Pedersen [26] found that the definitions were short, and did not contain enough overlaps to distinguish between multiple concepts. They extended this measure by including the definition of related concepts in WordNet.

Patwardhan and Pedersen [27] extend the measure proposed by Lesk using second-order co-occurrence vectors. In this method, a vector is created for each word in the concepts definition containing words that co-occur with it in a corpus. These word vectors are average to create a single co-occurrence vector for the concept. The similarity between the concepts is calculated by taking the cosine between the concepts second-order vectors.

## 3. Estimating WSD difficulty

### 3.1. Previous approaches

There has been little previous work on estimating the difficulty of WSD. Kilgarriff and Rosenzweig [28] analysed the difficulty of disambiguating terms used in the first SemEval WSD evaluation exercise [29] and found the entropy of the sense distribution to work well. This is calculated as follows:

$$Entropy(S) = -\sum_{i=1}^N Pr(s_i) \log_2 Pr(s_i) \quad (6)$$

where  $S = \{s_1, s_2 \dots s_N\}$  is the set of possible senses for some ambiguous term and  $Pr(s_i)$  the probability of sense  $S_i$  obtained from a labeled corpus.

In domain-independent WSD the Most Frequent Sense (MFS) is commonly used to indicate the difficulty of a particular term [30,31]. MFS is simply the sense that is found most frequently in a training corpus and is computed as follows:

$$MFS(S) = \arg \max_i P(s_i) \quad (7)$$

MFS is often used as a simple baseline for supervised WSD systems [32]. Like entropy, MFS also requires labeled training data.

Both of these approaches are based on the distribution of senses in text and the assumption behind them is that this information is a useful predictor of the difficulty of disambiguating that term. For example, consider an ambiguity where one of the senses is much more likely to appear than the others. The ambiguity will probably be easy to disambiguate, since always assigning the most probable sense will lead to reasonable WSD performance.

Stevenson and Guo [33] applied entropy and MFS to analyse the difficulty of automatically generating labeled WSD training data. However they did not explore whether they could be used to determine the difficulty of WSD for particular terms.

Stevenson and Guo [33] also made use of additional measures. One was the number of possible senses for the ambiguous term. The advantages of this measure is that it is very simple to compute and does not require any labeled training data. The intuition behind this approach is that ambiguities with a large number of possible senses will be difficult to disambiguate, simply because of the number of senses to choose from.

### 3.2. Pairwise similarity

Stevenson and Guo [33] also describe an approach that relies on computing the average pairwise similarity between the possible senses of ambiguous terms (see Section 2.2.1). Like counting the number of possible senses, this approach also has the advantage of not requiring any labeled training data.

The assumption behind this approach is that if the possible meanings of an ambiguous term are similar then that term will be more difficult to disambiguate than one where the meanings are clearly distinct. This is motivated by previous work on manual annotation of word senses which have shown that humans often struggle to distinguish between closely related meanings [13,34].

We extend this approach by considering the maximum similarity between senses in addition to the average. Two metrics were applied: *mean similarity* and *maximum similarity*. For the *mean similarity*, the degree of similarity between the concepts of each of the ambiguous word's possible senses is computed and combined by taking the mean of the similarities. This is calculated as follows:

$$\text{mean\_similarity}(S) = \frac{\sum_{\{s_i, s_j\} \in \binom{S}{2}} \text{sim}(s_i, s_j)}{\left| \binom{S}{2} \right|} \quad (8)$$

where  $S$  is the set of senses and  $\text{sim}(s_i, s_j)$  is the similarity between two of these senses as determined by one of the measures described in Section 2.2.

The *maximum similarity* measure is computed in a similar way. However, instead of taking the mean of the pairwise similarities the maximum is chosen:

$$\text{max\_similarity}(S) = \text{argmax}_{\{s_i, s_j\} \in \binom{S}{2}} \text{sim}(s_i, s_j) \quad (9)$$

### 3.3. Implementation

The 2009AB version of the Metathesaurus was used for the experiments described in Section 4. The pairwise similarity approaches described in Section 3.2 are implemented using the UMLS::Similarity package [35], a freely available open source Perl package.<sup>5</sup> Path information is obtained using the parent/child relations throughout the entire UMLS. The probabilities required by the IC-based measures are generated using the UMLSonMedline dataset. For the relatedness measures, the definition information is obtained from the concept definitions, as well as the definitions of its parent, child, narrower and broader relations, and its associated terms.

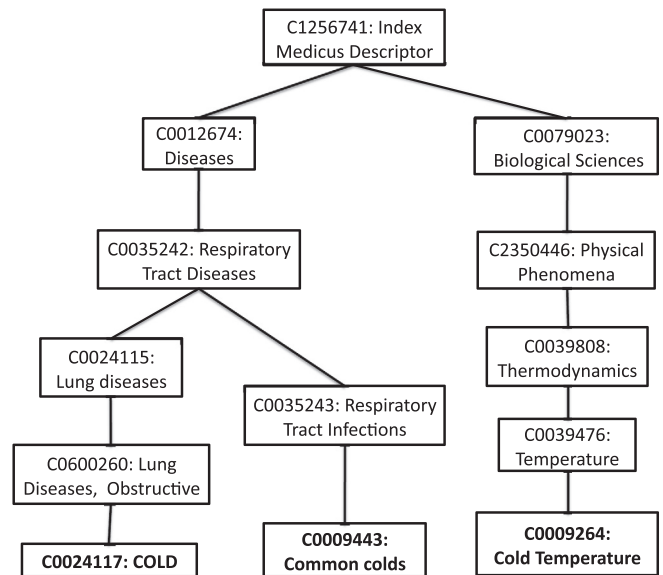
### 3.4. Example

In this section, we step through an example using the ambiguous term *cold*. In the UMLS, the possible senses for *cold* include Temperature, Cold [C0009264], the Common Colds [C0009443], or Chronic Obstructive Airways Disease [C0024117]; also referred to as the acronym COLD (Chronic Obstructive Lung Disease). Table 1 shows some of the UMLS Definitions for each of the above senses and Fig. 1 shows the CUIs and paths between each of the senses. The mean similarity for *cold* is calculated by first summing the similarity scores of each combination of senses and dividing it by its number of combinations. An example, using the path measure (see Section 2.2.1), is as follows:

$$\begin{aligned} \text{mean similarity} &= \frac{\sum_{x,y \in \binom{S}{2}} \text{sim}(x,y)}{\left| \binom{S}{2} \right|} = \text{sim}(\text{C0009264}, \text{C0009443}) \\ &+ \text{sim}(\text{C0009264}, \text{C0024117}) + \frac{\text{sim}(\text{C0009443}, \text{C0024117})}{\binom{3}{2}} \\ &= \frac{0.1111 + 0.1111 + 0.25}{\binom{3}{2}} = \frac{0.4111}{\binom{3}{2}} = 0.1574 \end{aligned} \quad (10)$$

**Table 1**  
Definitions of the possible senses of *cold*.

Term	UMLS CUI	Example UMLS Definitions
Temperature, Cold	C009264	An absence of warmth or heat or a temperature notably below an accustomed norm; Having less heat energy than the object against which it is compared; the absence of heat
Common Colds	C009443	A catarrhal disorder of the upper respiratory tract, which may be viral or a mixed infection. It generally involves a runny nose, nasal congestion, and sneezing
COLD	C0024117	A chronic, irreversible obstruction of air flow from the lungs. A disease of chronic diffuse irreversible air-flow obstruction



**Fig. 1.** Relationship between three senses of the term *cold* in the UMLS (2009AB version). Parent/child relations in the MeSH hierarchy are shown (e.g. C1256751 'Topical descriptor' is parent of C0012674 'Diseases' and C2930671 'Phenomena and Process').

## 4. Evaluation

We evaluated the approaches by determining how well they predict the accuracy of a WSD system on a set of ambiguous terms. Two WSD systems were used in our experiments: one supervised [36] (see Section 4.1.1) and one unsupervised [37] (see Section 4.1.2).

The accuracy of each approach was determined by ranking the terms using the approach and then comparing this with another ranking based on the accuracy of the WSD system. We compared the rankings using Spearman's Rank Correlation ( $\rho$ ). Spearman measures the statistical dependence between two variables to assesses how well the relationship between the rankings of the variables can be described using a monotonic function. Spearman's Rank Correlation was used rather than Pearson's because Pearson's assumes that the relationship between the data is linear. We used Fisher's  $r$ -to- $z$  transformation to calculate the significance between the correlation results.

### 4.1. Word sense disambiguation

#### 4.1.1. Supervised method

The supervised WSD system developed by Stevenson et al. [36] combines linguistic and biomedical specific features in a Vector

<sup>5</sup> <http://search.cpan.org/dist/UMLS-Similarity/>.



Space Model ([38]). A binary feature vector is created for each possible sense of the ambiguous term and the ambiguous term itself. A range of features are used including local collocations, salient bigrams, unigrams and MeSH terms. Local collocations are bigrams or trigrams containing the ambiguous term constructed from lemmas, word forms or part of speech tags. Salient bigrams are those bigrams with a high log likelihood score. Unigrams are lemmas of all content words in the sentence containing the ambiguous term. MeSH terms are indexing terms that had been manually assigned to each abstract for the purpose of indexing (see Section 2).

The sense of an ambiguous term is determined by computing the cosine between the vector representing the ambiguous term each of the vectors representing the senses. The sense whose vector has the smallest angle between it and the ambiguous term's vector is chosen as its most likely sense.

#### 4.1.2. Unsupervised method

We also used the unsupervised WSD system developed by McInnes et al. [37]. In their method, a second-order co-occurrence vector is created for each possible sense of the ambiguous term and the ambiguous term itself. The appropriate sense of the term is then determined by computing the cosine between the vector representing the ambiguous term and each of the vectors representing the sense. The sense whose vector has the smallest angle between it and the ambiguous term's vector is chosen as the most likely sense.

The vector for a specific sense is created by first obtaining a textual description of the possible sense. This consists of its definition, the definition of its parent/children and narrow/broader relations and the terms associated with the sense from the UMLS. Second, a word by word co-occurrence matrix is created where the rows represent the content words in the description and the columns represent words that co-occur with the words in the description found in MEDLINE abstracts. Lastly, each word in the sense's description is replaced by its corresponding vector, as given in the co-occurrence matrix. The average of these vectors constitutes the second order co-occurrence vector used to represent the sense. The second-order co-occurrence vector for the ambiguous term is created in a similar fashion by using the words surrounding the ambiguous term in the instance as its textual description.

## 4.2. Data

Evaluation was carried out using three data sets that include a range of ambiguous terms and abbreviations found in biomedical documents.

### 4.2.1. Abbreviation dataset

The “Abbrev” dataset<sup>6</sup> [39] contains examples of 300 ambiguous abbreviations found in MEDLINE that were initially presented by Liu et al. [40]. The data set was automatically re-created by identifying the abbreviations and long-forms in MEDLINE abstracts and replacing the long-form in the abstract with its abbreviation [39]. The abbreviations long-forms were manually mapped to concepts in the UMLS.

### 4.2.2. NLM-WSD dataset

The National Library of Medicine's Word Sense Disambiguation (NLM-WSD) dataset<sup>7</sup> contains 50 frequently occurring ambiguous words from the 1998 MEDLINE baseline [41]. Each ambiguous word in the NLM-WSD dataset contains 100 ambiguous instances randomly selected from the 1998 abstracts totaling to 5000 instances.

**Table 2**

Corpus statistics and overall disambiguation accuracies of WSD systems.

Dataset	WSD		Corpus statistics		
	Unsupervised	Supervised	# Senses	MFS	Entropy
NLM-WSD	0.52	0.91	2.3	0.78	0.45
Abbrev	0.91	0.98	2.6	0.70	0.82
MSH-WSD	0.78	0.97	2.1	0.54	1.00
Combined	0.75	0.96	2.10	0.67	0.89

The instances were manually disambiguated by 11 evaluators who assigned the ambiguous word to a concept in the UMLS (CUI) or assigned the concept as “None” if none of the possible concepts described the term.

### 4.2.3. MSH-WSD dataset

The National Library of Medicine's MSH Word Sense Disambiguation (MSH-WSD) dataset<sup>8</sup> contains 203 ambiguous terms and abbreviations from the 2010 MEDLINE baseline [14]. Each target word contains approximately 187 instances, has 2.08 possible senses and has a 54.5% majority sense. Out of 203 target words, 106 are terms, 88 are abbreviations, and 9 have possible senses that are both abbreviations and terms. For example, the target word *cold* has the abbreviation *Chronic Obstructive Airway Disease* as a possible sense, as well as the term *Cold Temperature*. The total number of instances is 37,888.

## 5. Results and discussion

### 5.1. WSD performance and corpus statistics

Table 2 shows the disambiguation accuracy of the WSD systems for each of the datasets (Abbrev, NLM-WSD and MSH-WSD) and their combination (Combine). The results show that overall the supervised system obtains higher disambiguation accuracies than the unsupervised one, which is consistent with previous results, for example [4–7]. They also show that the accuracy on the Abbrev dataset is higher than the MSH-WSD or NLM-WSD datasets. We believe this is because the Abbrev dataset contains only abbreviations, which have a more coarse grained distinction between their senses. We also see this between the MSH-WSD and NLM-WSD datasets. NLM-WSD primarily contains terms where, as mentioned above, MSH-WSD contains a mix of terms and abbreviations. This explains why the WSD systems obtain a higher disambiguation accuracy on the MSH-WSD dataset than the NLM-WSD dataset.

Table 2 also shows statistics for all three corpora, the average number of senses per ambiguous term (# Senses), the average MFS and the average entropy. There is not much variation in the average number of senses, with the number varying between 2.1 for MSH-WSD and 2.6 for NLM-WSD. The NLM-WSD dataset has the highest MFS and lowest entropy of the three corpora while the opposite is true for MSH-WSD. The differences in these statistics are due to the way in which these datasets were constructed. The NLM-WSD and Abbrev dataset use the sense distributions that are found in corpora which are often highly skewed. For example, all of the instances containing the term *association* in the NLM-WSD dataset are annotated with the same sense. However, the MSH-WSD dataset was created by selecting roughly the same number of examples of each possible sense. Consequently information about the sense distribution is less useful for MSH-WSD than it is for the other datasets.

<sup>6</sup> <http://nlp.shef.ac.uk/BioWSD/downloads/corpora>.

<sup>7</sup> The NLM-WSD and MSH-WSD (Section 4.2.3) datasets are available from <http://wsd.nlm.nih.gov>.

<sup>8</sup> Available from <http://wsd.nlm.nih.gov>.

**Table 3**  
Correlations with WSD accuracy.

Dataset	Measure	WSD	
		Unsupervised	Supervised
NLM-WSD	# Senses	<b>−0.30</b>	−0.17
	MFS	0.15	0.89
	Entropy	−0.17	<b>−0.88</b>
Abbr	# Senses	<b>−0.46</b>	−0.14
	MFS	0.18	<b>−0.57</b>
	Entropy	−0.33	0.32
MSH-WSD	# Senses	−0.05	−0.06
	MFS	<b>0.11</b>	0.14
	Entropy	<b>0.11</b>	<b>0.17</b>
Combined	# Senses	<b>−0.11</b>	<b>−0.11</b>
	MFS	−0.05	0.03
	Entropy	0.03	−0.09

### 5.2. Results for previous approaches

Table 3 shows the Spearman's Rank Correlations obtained when the WSD difficulty measures presented in Section 3.1 were compared against the WSD systems.

Overall these measures are better at predicting the accuracy of supervised WSD systems than unsupervised ones. For the NLM-WSD dataset there are high correlations between the accuracy of supervised WSD and two statistics (MFS and entropy). However, this is not surprising since both of these measures make use of information about the distribution of senses in labeled data, and this is the same data that is used to train the WSD system. Correlations using these measures are lower for the other two corpora, which have more balanced sense distributions.

Although the number of senses is not a good indicator of supervised WSD accuracy, it is better than the other measures at predicting unsupervised WSD accuracy on the NLM-WSD and Abbrev datasets. The MFS and entropy measures are not effective at predicting unsupervised WSD accuracy, presumably because the unsupervised WSD approaches do not make use of labeled training data.

This analysis suggests that measures such as MFS and entropy are strong indicators of WSD accuracy under some conditions, namely when the WSD system is supervised and the distribution of senses is skewed. However, both of these measures rely on labeled training data. Consequently they are not useful for predicting the accuracy of supervised WSD systems since the labeled data they require could simply be used to train a WSD model and the accuracy computed directly.

### 5.3. Results for similarity and relatedness measures

The pairwise measures (Section 3.2) were evaluated using the measures of similarity and relatedness described in Section 2.2.

**Table 4**  
Spearman's rank correlation results over the combined set.

Category	Measure	Unsupervised		Supervised	
		Mean	Max	Mean	Max
Path-based	path	−0.16	−0.19	−0.21	−0.24
	wup	−0.09	−0.11	−0.05	−0.07
IC-based	res	−0.10	−0.12	−0.17	−0.18
	jcj	−0.18	−0.19	−0.27	−0.27
	lin	−0.15	−0.16	−0.23	−0.23
Relatedness	a-lesk	<b>−0.33</b>	<b>−0.33</b>	<b>−0.48</b>	<b>−0.49</b>
	vector	−0.06	−0.09	−0.18	−0.23

Table 4 shows the Spearman's Rank Correlation results of the mean (Mean) and maximum (Max) similarity metrics compared to the accuracies from the supervised and unsupervised WSD systems for the combined data set. A positive correlation signifies that as the values of one variable increase, the values of the second variable also increase; a negative correlation signifies that as the values of one variable are increasing the other is decreasing. Our hypothesis is that the higher the similarity score the harder it is to disambiguate the ambiguous word. If this is true, we expect that terms with a high similarity score would have a lower disambiguation accuracy. Therefore, if the accuracies and the similarity scores of the ambiguous words in the datasets were correlated exactly we would see a correlation of  $-1.0$  (exact negative correlation).

Table 5 shows the  $p$ -values obtained from comparing the max-similarity results using the Fisher  $r$ - $z$  transform. Comparison between the measures using the supervised correlation results are in the upper triangle of the matrix and the unsupervised correlation results are in the lower triangle. (The  $p$ -values obtained using the mean-similarity are similar.) All  $p$ -values lower than 0.05 are considered to be significant and are printed in bold font.

The results show that the relatedness measure *lesk* obtains a statistically significantly higher negative correlation than the other measures ( $p \leq 0.05$ ). The *lesk* measure quantifies the similarity between the possible senses of a target word based on the overlap between the terms in their definitions. The results indicate that this is a better indicator of how difficult the senses are to distinguish between than the path information obtained from a taxonomy.

The results using the IC-based measures (*res*, *jcj* and *lin*) and the path measure (*path*) are comparable; there is no statistical difference between the scores ( $p \geq 0.26$ ). The path measure quantifies the degree of similarity between two concepts using the shortest path information. The IC-based measures extend this, by incorporating the probability of a concept occurring in a corpus. These results indicate extra information about the probability of a concept is not useful for determining the degree of WSD difficulty. Table 6 shows the top five least and most difficult terms to disambiguate and their scores using the Lin with the Mean Similarity Metric. For example, the term *cardiac pacemaker* has a similar score of 0.0004 indicating that the similarity between its possible concepts is low making it easier to distinguish between the senses. This is

**Table 5**  
Significance of spearman's rank correlations over the combined set for max similarity.

Measure	path	wup	res	jcj	lin	a-lesk	vector
path		0.03	0.26	0.33	0.47	<b>0.0006</b>	0.47
wup	0.18		0.10	0.28	<b>0.03</b>	<b>0.0000</b>	<b>0.03</b>
res	0.20	0.48		0.14	0.29	<b>0.0000</b>	0.56
jcj	0.47	0.20	0.22		0.30	<b>0.0023</b>	0.30
lin	0.34	0.31	0.33	0.38		<b>0.0004</b>	0.50
lesk	<b>0.05</b>	<b>0.005</b>	<b>0.006</b>	<b>0.04</b>	<b>0.02</b>		<b>0.0006</b>
vector	0.13	0.41	0.38	0.14	0.23	<b>0.003</b>	

**Table 6**  
Top 5 least and most difficult terms to disambiguate using *lesk* with the mean similarity.

Least Difficult		Most Difficult	
Term	Score	Term	Score
cardiac pacemaker	0.0004	aa	1.9448
cda	0.0004	fat	1.9713
extraction	0.0005	secretion	1.9910
determination	0.0007	radiation	2.2477
surgery	0.0007	fluid	2.8214

**Table 7**

Breakdown of spearman's rank correlation results on the datasets.

Dataset	Measure	Unsupervised		Supervised	
		Mean	Max	Mean	Max
NLM-WSD	path	−0.25	<b>−0.40</b>	−0.06	−0.14
	wup	−0.03	−0.21	−0.28	−0.35
	res	−0.12	−0.13	−0.32	−0.30
	jcn	0.03	−0.04	−0.07	−0.10
	lin	−0.10	−0.10	−0.31	−0.26
	lesk	<b>−0.30</b>	−0.29	<b>−0.44</b>	<b>−0.42</b>
	vector	0.002	−0.07	−0.22	−0.38
Abbrev	path	0.23	0.15	−0.13	0.01
	wup	0.29	−0.09	0.15	0.18
	res	0.23	0.07	−0.18	<b>−0.27</b>
	jcn	−0.11	−0.05	−0.19	−0.01
	lin	0.16	0.04	−0.13	−0.24
	lesk	<b>−0.23</b>	−0.15	<b>−0.39</b>	<b>−0.27</b>
	vector	−0.05	<b>−0.35</b>	−0.07	0.02
MSH-WSD	path	−0.22	−0.22	−0.32	−0.31
	wup	0.01	0.002	0.10	0.10
	res	−0.17	−0.18	−0.20	−0.21
	jcn	−0.25	−0.25	−0.35	−0.35
	lin	−0.19	−0.20	−0.25	−0.25
	lesk	<b>−0.41</b>	<b>−0.42</b>	<b>−0.57</b>	<b>−0.57</b>
	vector	−0.03	−0.06	−0.20	−0.21

contrary to *aa* which has a similarity score of 1.9448 indicating that the similarity between its possible senses are high making it more difficult to distinguish between them.

The path-based measure, *wup*, quantifies the degree of similarity based on the depth of the concepts in the hierarchy. The depth signifies the specificity of a concept; the deeper the concept the more specific it is. The results using *wup* show the correlation to the disambiguation accuracies are random, indicating that using the specificity of the possible senses of a word does not indicate the degree of difficulty to disambiguate it.

The relatedness measure (*vector*) quantifies the relatedness between the possible senses by looking at the context that surrounds the terms that surround the ambiguous word. Results indicate that this second order information is too broad to determine the difficulty of disambiguating between the senses of a target word.

The results also show that using the maximum similarity metrics obtains a higher or equal negative correlation than using the mean. Overall, the difference in the results is not significant ( $p \geq 0.05$ ) and either the maximum or mean of the individual similarity scores can be used to quantify the degree of disambiguation difficulty.

### 5.3.1. Results by data set

Table 7 shows the break down of the correlation scores on the NLM-WSD, Abbrev and MSH-WSD datasets individually. The strongest negative correlation is produced by the *lesk* measure in the majority of cases. For example, using *lesk* with the mean similarity measure results in a correlation of −0.57 for MSH-WSD and −0.44 for NLM-WSD. The picture is more mixed for the Abbrev data set where several of the correlation co-efficients are close to 0. This suggests that the measures are more useful for determining the WSD difficulty of terms than abbreviations.

Further analysis of how well the methods perform on terms and abbreviations was carried out on the MSH-WSD dataset. This dataset contains 203 target words where 106 are terms, 88 are abbreviations, and 9 have possible senses that are terms and abbreviations. Table 8 show the correlation results for each type of ambiguity in this data set. The supervised results show that there is little difference in the correlation results for abbreviations and terms. This indicates that it is able to determine the difficulty

**Table 8**Breakdown of Spearman's Rank Correlation on MSH-WSD using *lesk*.

MSH-WSD	Unsupervised		Supervised	
	Mean	Max	Mean	Max
Abbreviations	−0.26	−0.30	−0.32	−0.35
Terms	0.02	0.01	−0.30	−0.31
Terms/abbreviations	−0.94	−0.92	−0.48	−0.52

of disambiguating a target word regardless if it is a term or an abbreviation.

The unsupervised results show that it was unable to determine the difficulty of the terms in this dataset which is contrary to what was seen in the Abbrev results from Table 7. We believe the results from MSH-WSD may provide a more accurate indication on how well the unsupervised method works for two main reasons. The first is that the number of ambiguous abbreviations in the Abbrev dataset is low (16 abbreviations) compared with the MSH-WSD dataset (88 abbreviations). The second is that the disambiguation accuracies of abbreviations in the Abbrev dataset is smaller than those in the MSH-WSD dataset. The accuracies range from 0.96–1.00 in the Abbrev dataset to 0.89–1.00 in the MSH-WSD dataset.

## 6. Conclusion and future work

The accuracy of WSD systems for biomedical documents varies enormously across ambiguous terms. It would be useful to be able to predict the difficulty of a particular term for WSD systems in order to determine whether applying WSD would be useful. In this paper, we explore a range of approaches to estimating WSD difficulty. Some of these are based on information extracted from sense-labeled corpora while others make use of information from knowledge sources. Evaluation was carried out by comparing the predictions made by these measures with the actual accuracy of two different WSD systems on three data sets.

Results show that the supervised methods are good predictors of WSD difficulty in some cases, but that their results are not consistent across different data sets. These methods also require labeled training data, limiting their usefulness. The unsupervised approaches do not have this limitation and can be applied to a

wider range of ambiguities. Our experiments showed that these approaches were also good predictors of WSD difficulty. The best performance was obtained using the relatedness measure proposed by Lesk [25] and aggregating the scores using the mean similarity metric. This method obtained a statistically significantly higher negative correlation than the other measures when compared to both the supervised and unsupervised WSD systems ( $p \leq 0.05$ ). The performance of this measure was also reasonably consistent across different data sets and types of ambiguity (terms and abbreviations). The methods explored in this paper are useful tools for estimating the performance of a WSD system that can be computed without the need for labeled data.

In the future, we plan to explore other relatedness measures that use contextual information about the senses rather than (or in conjunction with) their placement within a taxonomy. We would also like to explore semantic groups of the terms to determine if some types are easier to disambiguate than others.

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